Ghost Detection and Removal in High Dynamic Range Images

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GHOST DETECTION AND REMOVAL IN HIGH DYNAMIC RANGE IMAGES

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ABSTRACT

A classic approach to obtain High Dynamic Range Images (HDRI) consists in combining multiple images of the same scene with varying exposures. However, if the scene is not static during the time of capture, moving objects will appear blurry and ghosted, i.e. in multiple locations. Detecting and removing ghosting artifacts is an important issue for automatic generation of HDRI of dynamic scenes. This paper first describes a new method for detecting regions where ghosting occur based on an order relation between pixel values in consecutive images. Secondly, we propose to use a robust statistics tool to remove the detected ghosts. Results with different scenes and comparison with two other methods show the effectiveness of the approach.

1. INTRODUCTION

A photograph taken with a conventional camera cannot capture the whole dynamic range of real scenes which varies over several orders of magnitude. As a consequence, some regions of the scene will be under- or over-exposed and appear, respectively, too dark or saturated in the image.

It is possible to capture an High Dynamic Range Image (HDRI) using multiple imaging devices, or devices that use special sensors [1]. For example, Mitsunaga and Nayar describe the process of spatially varying pixel exposures [2]. They place an optical mask adjacent to a conventional image detector array. The mask has a pattern with spatially varying transmittance, thus adjacent pixels on the detector are given different exposures to the scene. These kind of devices are still expensive and are not commonly used by the average consumer.

At present, a classic approach for obtaining an HDRI with a conventional camera is to take a sequence of images of the same scene with different exposure times, and combine them to a single radiance map [3, 1]. This multiple exposures technique suffers from two main problems:

1. *Misalignment:* if the camera moves during the time of capture, the images will be misaligned and the combined HDRI will look blurry.
2. *Ghosting:* if there are moving objects while capturing the sequence of images, these objects will appear in different locations in the combined HDRI, creating what is called *ghost* or *ghosting* artifacts.

The first problem can be solved by placing the camera on a tripod or by using an image registration method. In particular, the median threshold bitmap (MTB) technique proposed by Ward [4] is very efficient for that purpose. The method is fast and can accurately recover the small displacements between images.

The second problem is a severe limitation of the multiple exposures technique since motions are hardly avoidable in outdoor environments. Roughly speaking, we can identify two types of motion in a dynamic scene: (i) a moving object on a static background; examples are moving people or cars. (ii) a moving background with static or dynamic objects; typical examples are landscapes with moving leaves, or water ripples.

Detecting and removing ghosting artifacts created by motion is an important issue for automatic generation of HDRI of dynamic scenes. One example of HDRI generation with both moving object and water ripples is shown in Fig. 1, 2 and 3. The ghosting artifacts created by the moving boat are clearly visible on Fig. 3.a, and artifacts created by water ripples are visible on Fig. 3.b. This paper introduces an efficient and fast method for detecting the regions where ghosting might occur. Our approach makes use of the order relation between pixel values in differently exposed images to detect possible gohsting regions, without the need of precomputing the camera response function. Ghost are then eliminated in the detected regions using a robust statistics tools, the quasi-continuous histograms (QCH) framework.

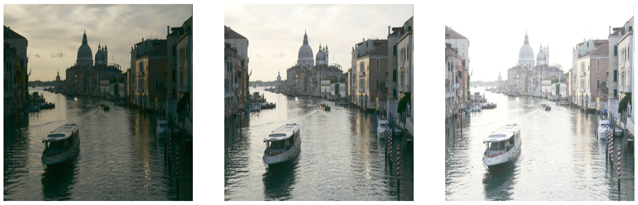
The remainder of this paper is organized as follows: we describe some previous work on ghost detection and removal, and describe our proposed methods for detecting and removing ghost regions in Section 2. In Section 3, we show some experimental results and compare our method with previous ones. Finally, we conclude and give some perspectives in Section 4.

2. GHOST DETECTION

2.1 Previous work on ghost detection

There exist some previous work which address the problem of ghost detection and removal in HDRI generation. There are methods which first detect regions where ghosting might occur, and then, use a single exposure image to represent these regions [1]. Other methods are based on an explicit estimation of the motion of moving objects. These include optical flow techniques to warp pixels in the exposures images so that all scene features are correctly aligned [5]. Motion detection methods are suitable for the first type of motion, i.e. a moving object on a static background, but fail for the second type of motion. Recently, Khan *et al.* [6] propose a method to generate ghost-free HDRI without the need for explicit object detection and motion estimation.

The method is based on an iterative estimation of the weights assigned to each pixel according to its chance of belonging to the static part of the scene. The method is slow and fails if the scene does not predominantly captures a static



(a) (b) (c)

Figure 1: Three exposures of a dynamic scene. Exposure times are respectively: a) 1/750 s, b) 1/180 s and c) 1/45 s.

Figure 2: The tonemapped HDRI generated with the three images of Fig. 1.

background.

In this work, we focus on the methods which first detect regions where ghosting might occur. One solution for detecting possible ghost regions is based on computing the weighted variance at each pixel location and selecting regions where this local variance is above a defined threshold [1]. For each of the detected regions, a single exposure is selected and its radiance values are used in the HDRI. This approach works well when the moving object is significantly different from the background in terms of contrast. For regions where the object colour is similar to the background, the method fails to detect moving objects. A similar method is described by Jacobs *et al.* [7] who defines two types of motions, HCM (High Contrast Movement) and LCM (Low Contrast Movement). The former type of motion occurs when the moving object is different from the background and is detected based on a measure of variance as in [1]. The later type of motion occurs when the dynamic object and the background are similar and is detected using a measure derived from entropy. Since entropy is insensitive to the level of contrast in the data, this solution works wells for LCM. However, some regions with high entropy but no motion are misclassified as LCM as well [7].

Another solution for detecting possible ghost regions is given by Grosch [8] who uses the camera response function to predict the colour of a pixel from one image to another with a different exposure time. More precisely, for each pair of consecutive images I_1 and I_2, one tests if the colour of a pixel in I_2 is well approximated by the predicted colour from I_1. The test is based on a defined threshold value, and a significant difference between two colours indicates object motion.

(a) (b)

Figure 3: a) An example of ghosting due to the moving boat, b) An example of artifacts due to water ripples.

2.2 Proposed detection method

The brightness of a pixel in an image is related to the scene radiance and to the time of exposure. If we suppose an ideal imaging system with linear radiometric response, then the brightness Z will be related to scene radiance L by the following equation [9]:

$$Z = L\frac{cos^4\phi}{h^2}E, \tag{1}$$

where h is the focal length of the imaging lens, ϕ is the angle of the principal ray from the optical axis and E is the exposure of the image which is given by:

$$E = \frac{\pi d^2}{4}t, \tag{2}$$

where d is the aperture size of the imaging lens and t is the duration of exposure.

In practice, several stages of image acquisition process introduce non-linearities so that the response function is not linear. There are methods to recover this response function from a sequence of differently exposed images [3, 9, 10]. For our purpose, it is sufficient to assume that the response function is monotonic, which is a reasonable assumption [3].

Let now suppose that we have two images I_1 and I_2 with respective exposure times Δt_1 and Δt_2, such that $\Delta t_1 < \Delta t_2$. Using equation (2), we can show that for any pixel j in the two images, the respective exposure values $E_{j,1}$ and $E_{j,2}$ satisfy the following relation:

$$E_{j,1} \leq E_{j,2}. \tag{3}$$

Then, following equation (1), the pixel values in the two images, $Z_{j,1}$ and $Z_{j,2}$, are related by the following relation:

$$Z_{j,1} \leq Z_{j,2}. \tag{4}$$

This order relation can be generalized for a higher number of images. If we have N exposures I_k, with $k \in [1,\ldots,N]$, then for any pixel at location j in the N images the following relation should be respected:

$$Z_{j,k} \leq Z_{j,k'}, \text{ if } k < k'. \tag{5}$$

Ghosting regions are detected based on the observation that the order relation given by equation (4) is satisfied for pixels which remain static between two images, and can be broke down for moving pixels. Therefore, we detect possible ghosting regions by checking the order relation between

k consecutive images, and by marking pixels for which the relation breaks down at least once.

It is important to point out that this rule will not only detect moving objects, but any unexpected variation of a pixel's colour through the sequence of images as well. For instance, the case of rippling water where a particular pixel on the water oscillates between being in the shadows or under the sun. This kind of artifacts is hard to detect since there is no motion as illustrated in Fig. 3.b.

The order relation only works if the pixel is not under- or over-exposed. For instance, a white pixel in a shorter exposure will remain white in a longer exposure, and a black pixel in a longer exposure remains black in a shorter one. Therefore, we discard under- and over-exposed pixels when checking the order relation between consecutive images. Concretely, we exclude pixels which are outside the range $[20, \ldots, 240]$, pixels values varying from 0 to 255.

2.3 Ghost-free HDRI generation

Once ghost regions are detected, artifacts-free HDRI can be created. For all pixels outside a ghosting region, HDRI generation proceeds in a conventional manner, i.e. the pixel value in the HDRI is a weighted average of the corresponding pixels in the differently exposed images. For a pixel inside a detected ghosting region, a common approach is to substitute the pixel value by the corresponding value in the best exposure image for that region. For each region, the best exposure is chosen as the one with the lowest number of under- or over-exposed pixels. If this method gives goods results in some cases, it, unfortunately, reduces the dynamic range of the HDRI by considering only one exposure.

Our ghost-free HDRI generation approach relies on identifying, for each pixel location j, in the detected regions, two sets of exposures: W_j and H_j. The former is the set of exposures which contain the moving object at location j, while the later represents exposures that do not contain the moving object at location j. Therefore, combining only exposures in H_j lead to a ghost-free HDRI.

We detect these two sets of exposures for each pixel location using the quasi-continuous histograms (QCH) framework [11]. For each pixel location, we consider the N pixel values in the different exposures as N observations and use QCH to estimate the main mode of the uderlying distribution. Here, we make the assumption that the moving object appears in a small number of images at the location, i.e. for each pixel location j the cardinal of W_j is greater than the cardinal of H_j. This assumption, which is also used in Khan's method [6], ensures that the main mode of the distribution captures the static part of the scene and not the moving object. However, this assumption implies a minimum number of images. In our experiments, we use a least 5 five images to create an HDRI.

3. EXPERIMENTAL RESULTS

We tested our method with various scene types. A tripod was used for capturing the sequences of images, in order to keep the camera stable and avoid misalignment. So, we are interested in detecting motion in the scene being captured. As mentioned before, motion can be caused either by a moving object on a static background or by movements of the background itself. Fig. 4 shows the result of our algorithm applied to the sequence of images presented in Fig. 1. As we can observe, both the moving boat and water ripples are detected by the algorithm.

Figure 4: Ghost regions detected by the proposed method. Pixels that violate the order relation are markes in white.

We compare our method with the variance-based approach [1, 7] and with the predicted colour method [8]. We obtained similar results with all of the three methods, but one main advantage of the proposed method is that it does not require the user to specify a threshold. Finding the correct threshold for a sequence of images is not a trivial issue. In [1], the authors suggest to use the value 0.18 as threshold for variance values varying in the interval $[0, 1]$. However, this empirical value is not suitable for all scenes. Fig. 5 shows different results obtained with the variance-based method using different threshold values. A low threshold produces false detections (Fig. 5.a) while a high threshold loses some ghosting regions (Fig. 5.b).

In the example shown in Fig. 6, the ghosting regions are more localized. Only some leaves on the branches are in motion during the time of capture. With the threshold-based methods, a low threshold will result in many false detections, i.e. detecting static parts of the scene as possible ghosting regions. Since a single exposure is selected per ghosting region to creat a ghost-free HDRI, as explained in Section 2.3, there will be an important lost of dynamic range of the combined image. The proposed method, based on an order relation between pixel values in different exposures, can detect, almost precisely, the small ghosting regions in the image. We therefore, minimize the loss of dynamic range of the final combined HDRI when using the single exposure technique. Detection results for this sequence are shown in Fig. 7. The good results for the variance-based and the predicted colour methods, Fig. 7.a and b, where obtained after trying several threshold values. On the contrary, the order relation based method, Fig. 7.c, does not require a threshold.

Our experiments, with various sequences, show that the order relation-based method and the predicted colour method give more precise results than the variance-based method. This is because the variance measure works well only if the colour of the moving object is clearly distinguishable from that of the background.

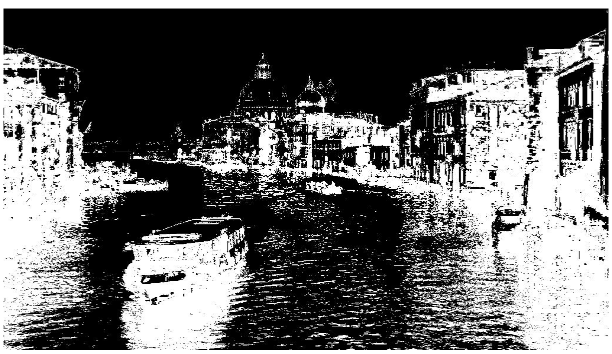
Fig. 8 shows an example of ghost-free HDRI generation using quasi-continuous histograms method in the detected ghosting regions. As can be seen, the cyclist has been correctly removed. On the other hand, the man on the left of the image is not completely removed since he appears in a larger number of images at each location.

(a_1) (a_2) (a_3) (a_4) (a_5)

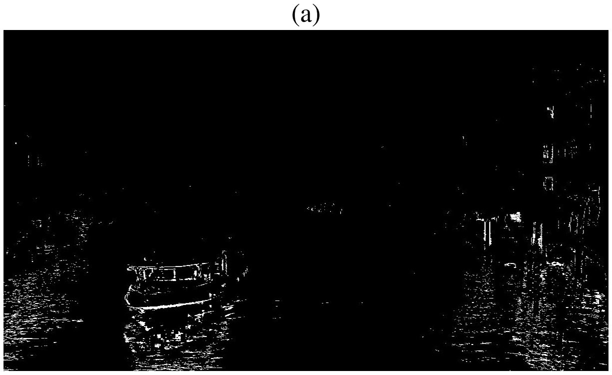
(b)

(c)

Figure 6: a) Five exposures of a scene with moving leaves, b) The tonemapped HDRI generated from these fives images, c) An example of region where ghosting occur.



(a)



(b)

Figure 5: Ghost regions detected by the variance-based method [1, 7]: a) Detection with a threshold of 0.18, b) Detection with a threshold of 0.3.

4. CONCLUSION AND FUTURE WORK

In this paper, an efficient method for detecting ghost regions in HDRI is presented. The method is based on an order relation between pixels values in differently exposed images. Experimental results show that the method can accurately detect either moving objetcs or small backgroung motion. Futhermore, it does not require to specify a threshold value as opposed to other approaches. The proposed method can then automatically classify pixels in two groups. For pixels in the first group, with no motion, we can apply a classic HDRI generation process. For pixels in the second group, we remove the gohsting while preserving the high dynamic range of the images, using a quasi-continuous histograms method.

Our future work will intend to emply the quasi-continuous histograms method to reduce noise in HDRI.

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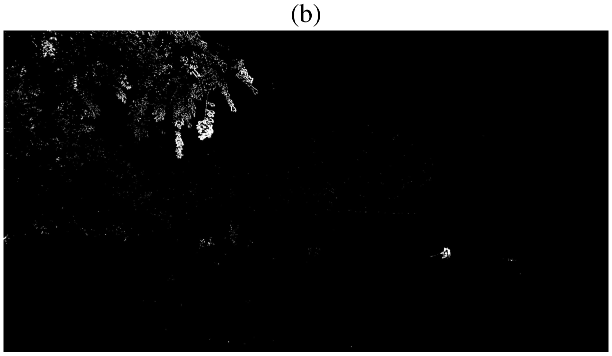
(a)

(b)



(c)

Figure 7: Ghost regions detection results with the images of Fig. 6: a) Detection with the variance method, b) Detection with the predicted color method, c) Detection with the proposed method.

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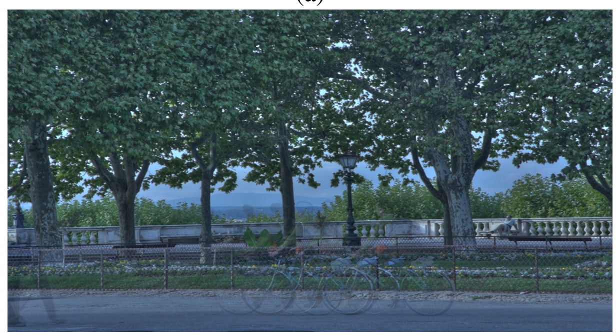
(a)



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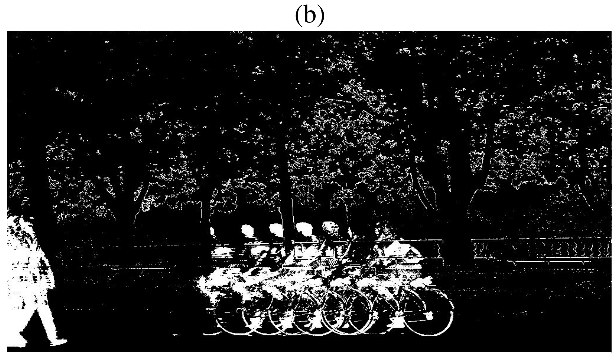

(c)

(d)

Figure 8: Ghost-free HDRI generation: a) Four exposures of a sequence which contains seven images. b) HDRI generated with ghosting artifacts. c) Ghost region detected with the proposed method, c) Ghost-free HDRI generated.